Terrain categorization using LIDAR and multi-spectral data

Angela M. Puetz, R. C. Olsen, Michael A. Helt
U.S. Naval Postgraduate School, 833 Dyer Road, Monterey, CA 93943
ampuetz@nps.edu, olsen@nps.edu

ABSTRACT

LIDAR data taken over the Elkhorn Slough region in central California were analyzed for terrain classification. Data were collected on April 12th, 2005 over a 10 km x 20 km region that is mixed use agriculture and wetlands. LIDAR temporal information (elevation values), intensity of returned light and distribution of point returns (in both vertical and spatial dimensions) were used to distinguish land-cover types. Terrain classification was accomplished using LIDAR data alone, multi-spectral QuickBird data alone and a combination of the two data-types. Results are compared to significant ground truth information.

Keywords: LIDAR, multi-spectral, Elkhorn Slough, terrain classification

1. INTRODUCTION

The goal of this research is to analyze the utility of LIDAR data for ground classification purposes. LIDAR data were analyzed alone and in conjunction with multi-spectral data.

LIDAR data used in this study were collected by Airborne 1 Corporation using the Optech ALTM (Airborne Laser Terrain Mapper) 2025. DigitalGlobe® collected multi-spectral data using the QuickBird sensor. The specifications for both data sets are below (Tables 1a and 1b).

Table 1a. Specifications for Airborne 1 LIDAR data collect.

Airborne 1 LIDAR Collection Parameters	
Collection rate	25,000 pulses per second
Wavelength	1064 nm (NIR)
Collection dates	April 12th, 2005
Altitude	1828 m
Strip width	+/- 18°, 1200 m Ground Swath
Pulse Return Classification	1 - Extracted Feature - Last Pulse 2 - Bare Earth - Last Pulse 3 - Extracted Feature - First Pulse 4 - Bare Earth - First Pulse
Point spacing	1-m posting gridded to 2.4-m
Platform	ParteNavia fixed-wing twin prop
Datums	UTM Zone 10, NAD83, NAVD88 m

Table 1b. Specifications for QuickBird multi-spectral data collect.

QuickBird Multi-Spectral Collection Parameters	
Wavelengths	Blue – 479.5 nm Green – 546.5 nm Red – 654 nm Near IR – 814.5 nm
Collection dates	Oct 8th, 2002
GSD	2.4 x 2.4 m
Level of processing by vendor	Standard 2A

2. BACKGROUND

To derive elevation values from LIDAR data, a measurement is made of the time lapse between when a laser pulse is emitted and when the reflected light reaches the sensor again. Multiplying the speed of light by the elapsed time gives the distance between the sensor and the object being sensed. Combining the 'distance traveled' information with the GPS and INS data onboard the aircraft allows the calculation of precise elevation values of objects on the ground.

Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XIII,
edited by Sylvia S. Shen, Paul E. Lewis, Proc. of SPIE Vol. 6565
65650V, (2007) · 0277-786X/07/$18 · doi: 10.1117/12.719885

Downloaded from SPIE Digital Library on 20 Aug 2010 to 205.155.65.226. Terms of Use: http://spiedl.org/terms

Report Documentation Page

Form Approved
OMB No. 0704-0188

Public reporting burden for the collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.

1. REPORT DATE **2007**	2. REPORT TYPE	3. DATES COVERED **00-00-2007 to 00-00-2007**

4. TITLE AND SUBTITLE **Terrain categorization using LIDAR and multi-spectral data**	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Naval Postgraduate School,833 Dyer Road,Monterey,CA,93943**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR’S ACRONYM(S)
	11. SPONSOR/MONITOR’S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT
LIDAR data taken over the Elkhorn Slough region in central California were analyzed for terrain classification. Data were collected on April 12th, 2005 over a 10 km x 20 km region that is mixed use agriculture and wetlands. LIDAR temporal information (elevation values), intensity of returned light and distribution of point returns (in both vertical and spatial dimensions) were used to distinguish land-cover types. Terrain classification was accomplished using LIDAR data alone, multi-spectral QuickBird data alone and a combination of the two data-types. Results are compared to significant ground truth information.

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Same as Report (SAR)**	**6**	

LIDAR data can also be used to determine something about the physical structure of an object. When pulse of light interacts with objects on the ground and with the atmosphere it travels through, the shape of the pulse is affected. As an example, consider a tree on the ground. Some of the light that hits the tree will be reflected from the very top of the tree, while some of the light will continue to filter further down through the canopy before it is reflected back to the sensor. The reflection of light at slightly different times creates a variation in light intensity being recorded over time at the sensor. This signal, which represents the way in which light interacts with objects on the ground, can be used to distinguish and identify materials.

Full-return LIDAR systems record the entire signal return for later processing, while discrete-return LIDAR systems record a small number of samples from the returned signal. Discrete returns are measured by finding the 'edges' in the return signal, under the assumption that objects at different heights within the same spatial resolution cell will be distinguished.

3. PROCESSING

The LIDAR data set used in this study was from a discrete-return system. Up to four elevation values and four associated intensity values were recorded for each point on the ground. The points at each ground location were classified into one of four classes as part of the processing at Airborne 1: Extracted Feature – Last Return; Bare Earth – Last Return; Extracted Feature – First Return; or Bare Earth – First Return.

The Bare Earth – Last Return features were used to create a DEM of the bare earth using IDL 'trigrid' and 'triangulate' routines. These routines are IDL's solution to the problem of irregularly gridded data (4). This DEM was then used to register the QuickBird multi-spectral data.

The QuickBird data used in this study was a DigitalGlobe® Standard Imagery Product. This data type has a rough DEM applied as part of the post-processing (3), making it unsuitable for precision orthorectification. Because orthorectification wasn't possible, the QuickBird image was registered to the LIDAR DEM. This method does not necessarily create an image that accurately reflects the ground, but does allow comparison of QuickBird pixels to LIDAR data points based on their geolocation. The accuracy of the registration varied over the scene area. Small sections of the overall scene that exhibited excellent registration were chosen for analysis (Figures 1a and 1b).

Fig. 1a. Segment of the QuickBird multi-spectral image.

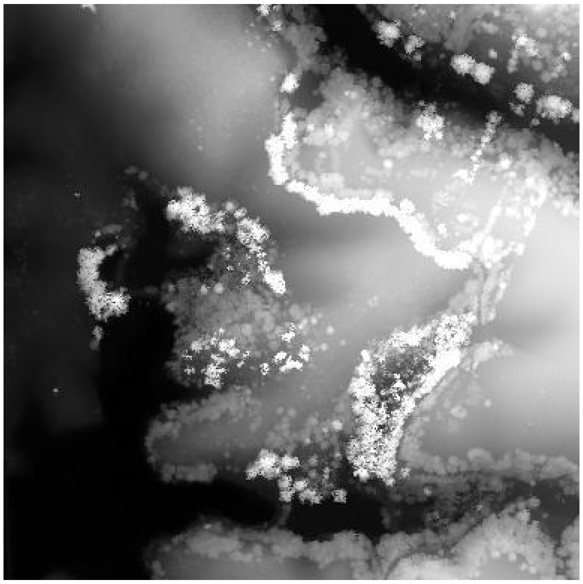

Fig. 1b. Geographically same area of Airborne 1 LIDAR image (Extracted Feature – First Return).

Downloaded from SPIE Digital Library on 20 Aug 2010 to 205.155.65.226. Terms of Use: http://spiedl.org/terms

4. RESULTS AND ANALYSIS

The most obvious way to use LIDAR data in conjunction with multi-spectral imagery is to look at materials that exhibit similar spectral features but have differing height characteristics. There are abundant Eucalyptus and Oak woodland areas in the Elkhorn Slough region. While these materials look very similar from above, they actually have very different physical characteristics.

The Normal Difference Vegetation Index (NDVI) was used to create a healthy vegetation mask. Several vegetated areas were chosen as ground truth sites. The Regions Of Interest (ROIs) overlaid on the image below (Figure 2) mark the ground truth locations in this image segment.

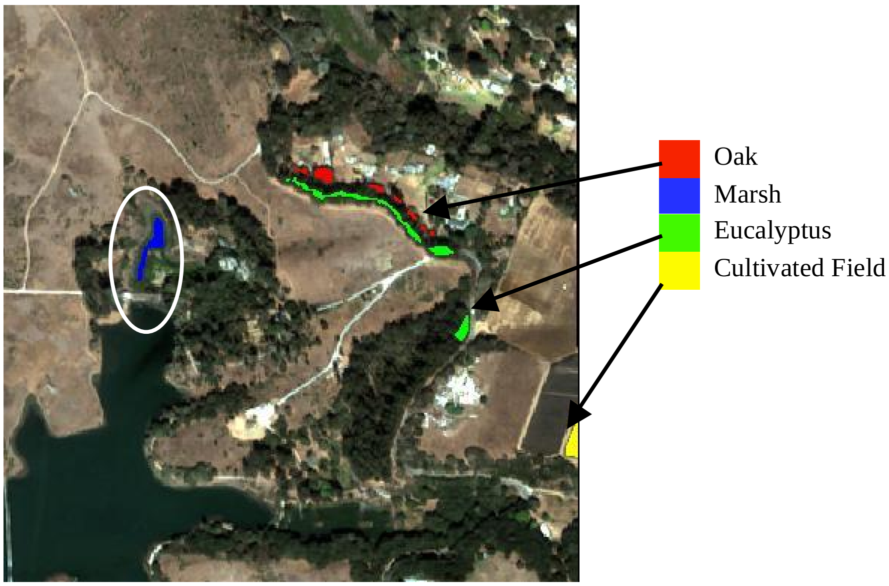

Fig. 2. QuickBird multi-spectral image with overlaid healthy vegetation ROIs.

The vegetation spectra look very similar in the multi-spectral imagery because they all exhibit the characteristics of ‘healthy vegetation’. In the LIDAR data however, we can more easily separate the different types of vegetation based on differences in heights and intensity of light from the reflected LIDAR pulse (Figures 3a-c and Table 2).

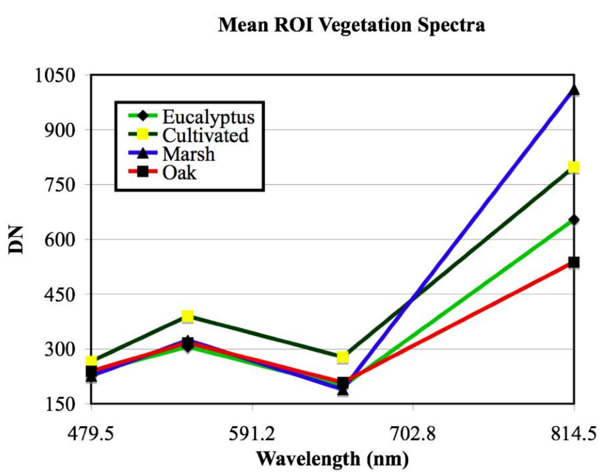

Fig. 3a. Vegetation spectra over QuickBird multi-spectral wavelength range. The values shown are the mean values of the ROIs above.

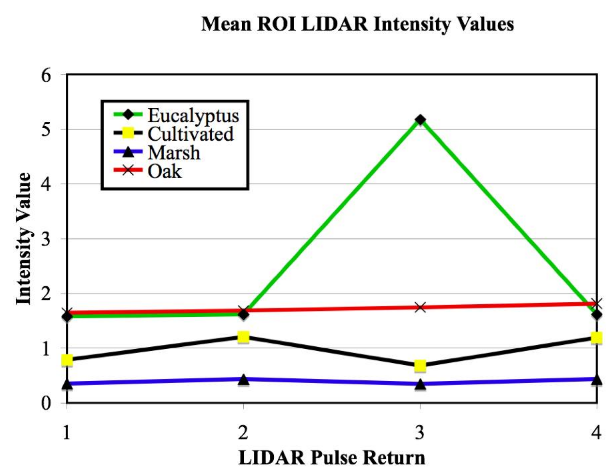

Fig. 3b. Four LIDAR intensity values for the healthy vegetation ROIs.

Downloaded from SPIE Digital Library on 20 Aug 2010 to 205.155.65.226. Terms of Use: http://spiedl.org/terms

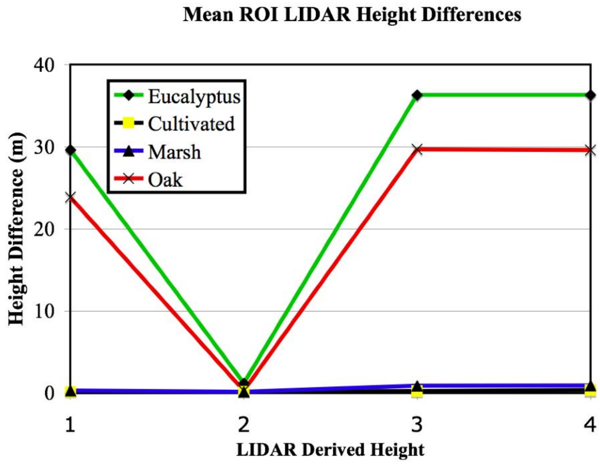

Fig 3c. LIDAR derived height values and ranges.

Table 2. Data points for Figure 3c, LIDAR derived height values and ranges. EF = Extracted Feature Return, BE = Bare Earth Return.

Mean ROI LIDAR Height Differences				
	EF 1^{st} – EF Last	BE 1^{st} – BE Last	EF 1^{st} – BE 1^{st}	EF 1^{st} – BE Last
Eucalyptus	29.63	1.19	36.31	36.31
Cultivated	0.12	0.16	0.26	0.35
Marsh	0.30	0.14	0.89	0.90
Oak	23.86	0.26	29.67	29.60

In order to analyze the effectiveness of adding LIDAR information into image classification schemes, information for the separate data types (multi-spectral, LIDAR height, LIDAR intensity) were combined. The different data types have widely different ranges of values. In order to minimize this effect, the top and bottom 2% of the tails of the histogram of values for each data type were excluded. The remaining values were scaled from 0-255. The bands of spectral data were then combined with the bands of LIDAR information into one image file.

The data was classified using the Maximum Likelihood classification scheme from the ENVI software. The classification was done using information from each data type individually and in combination (Figures 5a-d).

ENVI was used to create a confusion matrix using the ground truth ROIs. The classified image pixels were compared to the ROI pixels and a measure of overall classification accuracy was calculated (Table 3).

Table 3. Overall classification accuracy based on ground truth ROIs.

	4-band MSI (Fig. 5a)	4-pulse return Height (Fig. 5b)	4-pulse return Intensity (Fig. 5c)	Height and Intensity	MSI, Height, and Intensity (Fig. 5d)
Percentage correctly classified	88.47	65.74	69.84	80.93	89.14
# of pixels (correct/total)	798/902	593/902	630/902	730/902	804/902

The highest classification accuracy was obtained by using all of the available information in conjunction. The addition of LIDAR information did not lead to a dramatic increase in overall classification accuracy. It is notable that the classification of LIDAR Height and Intensity information created an accuracy of 80.9%, which is close to what is achieved using the multi-spectral data.

Downloaded from SPIE Digital Library on 20 Aug 2010 to 205.155.65.226. Terms of Use: http://spiedl.org/terms

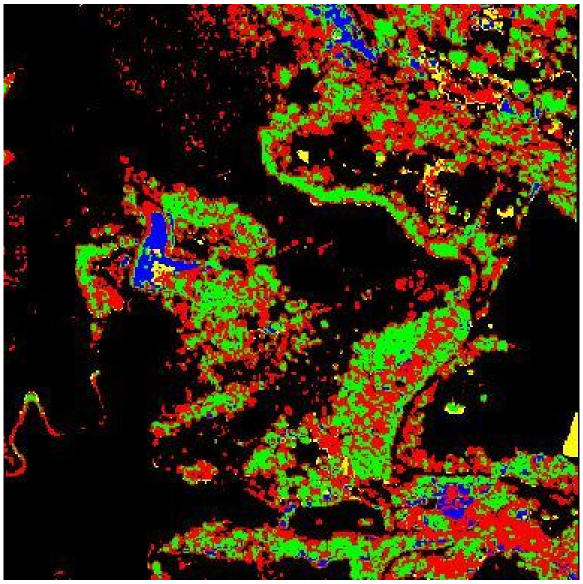

Fig. 5a. Maximum Likelihood classification using 4-bands of multi-spectral data only.

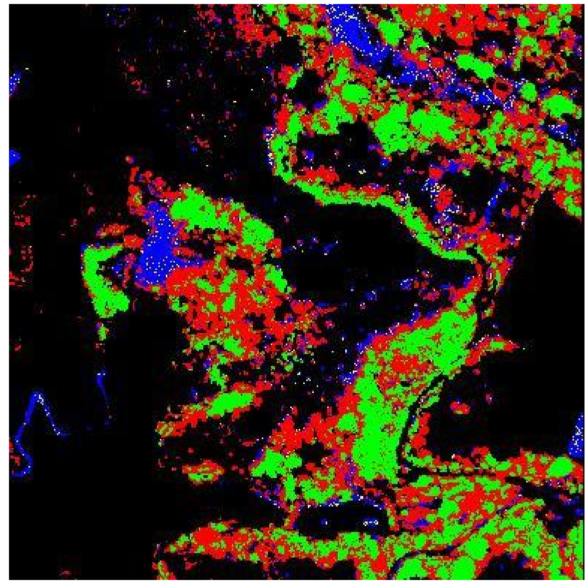

Fig. 5b. Classification using 4 bands of LIDAR derived height information only.

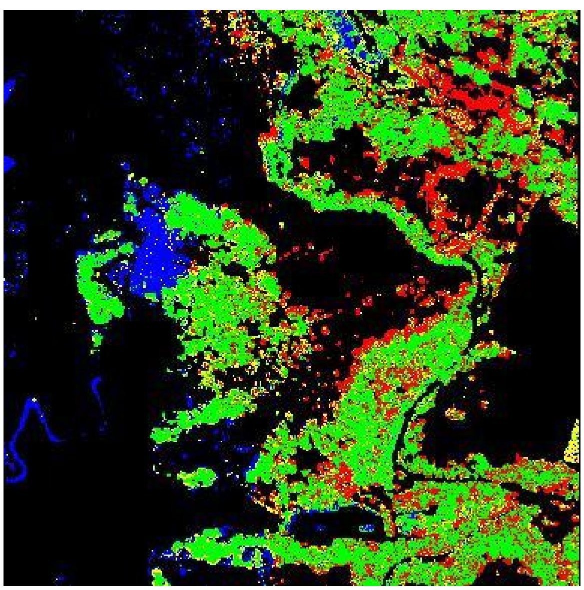

Fig. 5c. Classification using LIDAR Intensity information only.

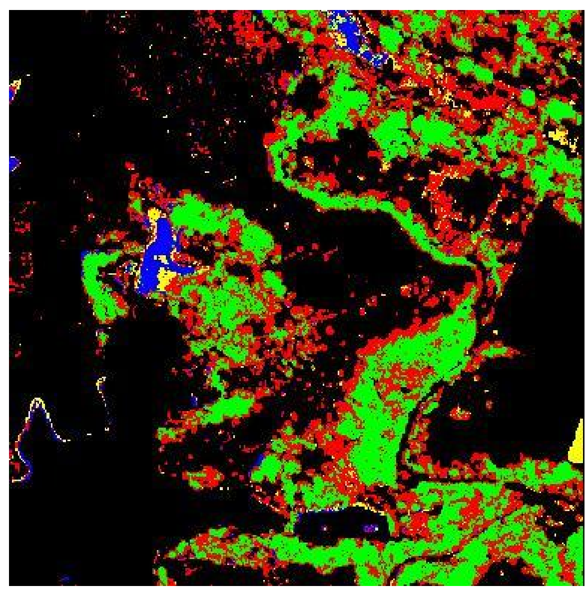

Fig. 5d. Classification of combined data product (multi-spectral, LIDAR-derived heights and LIDAR intensity).

Downloaded from SPIE Digital Library on 20 Aug 2010 to 205.155.65.226. Terms of Use: http://spiedl.org/terms

5. FUTURE WORK

Based on the success of using discrete-return LIDAR information for image classification, it is realistic to think that useful information can be extracted from full-waveform LIDAR data using traditional spectral image processing techniques. An attempt was made to simulate full-waveform LIDAR data from the discrete-return LIDAR data used in this study. A histogram was created based on all LIDAR returns within a small spatial extent, but this led to smoothing in the spatial dimension. While it was possible to distinguish different classes of materials using this technique, the spatial resolution was degraded beyond a point that is interesting in this type of terrain classification.

REFERENCES

1. Helt, M., Vegetation Identification with LIDAR, MS Thesis, Naval Postgraduate School, September 2005.
2. Helt, M., Olsen, R. C., Puetz, A. M., Analysis of LIDAR and spectral imagery for scene classification in forested areas, SPIE paper 6233-62, 2005.
3. QuickBird Imagery Products – Product Guide, Revision 4.7.2, DigitalGlobe®, Inc., 2006.
4. IDL Reference Guide, IDL Version 6.2, July 2005 Edition

Downloaded from SPIE Digital Library on 20 Aug 2010 to 205.155.65.226. Terms of Use: http://spiedl.org/terms